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Enhancing Image Quality Assessment combining CNN: A Review of Methods and Applications

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***Abstract –** This paper explores Convolutional Neural Networks (CNNs) in image quality assessment (IQA), emphasizing their potential to enhance image processing across industries. Due to the limitations of conventional metrics such as peak signal-to-noise ratio (PSNR) and mean square error (MSE), CNNs are being investigated for IQA. Despite challenges like data requirements and transparency, CNN-based IQA offers significant advantages. The paper discusses how CNNs handle complex distortions and emphasizes the need for diverse evaluation metrics to assess their effectiveness. Understanding CNN-based IQA's capabilities is crucial for its integration into image processing systems.*

Keywords- Image quality assessment, Convolutional Neural Networks, traditional metrics, performance evaluation

I. INTRODUCTION

In recent years, image processing has become crucial across industries like healthcare, security, and entertainment, where the quality of input images directly impacts system accuracy and efficiency [1]. Traditional metrics like MSE and PSNR, while widely used, have limitations in assessing human-perceived image quality, leading to the exploration of deep learning, in particular Convolutional Neural Networks (CNNs), for Image Quality Assessment (IQA) [2]. This paper reviews the advancements and challenges of CNN-based IQA techniques, emphasizing their potential to handle complex distortions. It also highlights the need to evaluate CNN-based models using diverse metrics to understand their effectiveness compared to traditional methods. Understanding the capabilities and limitations of CNN-based IQA models is vital for their integration into image processing systems across various domains [3].

II. LITERATURE REVIEW

Recent advancements in image processing have been marked by innovative techniques and methodologies that leverage deep learning and convolutional neural networks (CNNs). Kim et al. (2017) introduced a high-resolution image technique employing a deeply-recursive convolutional network with skip connections and recursive supervision, demonstrating improved super-resolution performance with increased recursion depth [4]. Building on this, J Kim et al. (2016) presented a comprehensive approach for single-image super-resolution, emphasizing the utilization of deep convolutional networks to enhance accuracy and efficiency [5].

Christian Ledig et al. (2017) set a new standard for one-image super-resolution, prioritizing perceptual quality and achieving photo-realistic results [6]. In the context of medical imaging, J J MA et al. (2020) emphasized the critical need for automated frameworks to evaluate image quality, particularly in MRI, for diagnostic purposes [7]. Kai Zhang et al. (2017) addressed image restoration in low-level vision applications by combining optimization with deep convolutional neural network denoiser priors [8].

Recent studies by Keyan Ding et al. (2021) focused on the use of objective image quality assessment models as enhancement objectives in image processing tasks, underlining their performance in real-world applications

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[9]. Santhi N et al. (2019) explored deep learning approaches in image evaluation, with a particular emphasis on image segmentation and computer-aided analysis, showcasing the transformative potential of deep learning in image analysis [10].

In the medical imaging domain, S. Suganyadevi et al. (2022) highlighted the profound impact of deep learning techniques, specifically in the identification, classification, and quantification of trends in various medical imaging domains [11]. The study underscores the rapid growth of deep learning in medical image processing, ranging from radiology to musculoskeletal imaging.This synthesis of recent research underscores the multidimensional applications of deep learning in image processing, offering insights into super-resolution, image quality assessment, and the transformative role of deep learning in medical imaging.

Research Objectives: This research aims to comprehensively review and analyze Convolutional Neural Network (CNN)-based methods for enhancing image quality assessment. The objectives include investigating existing CNN architectures used in image quality assessment, analyzing their impact on super-resolution techniques, evaluating their role in prioritizing perceptual quality, particularly in achieving photo-realistic results. Additionally, the study seeks to understand the transformative influence of CNNs in medical image processing, focusing on tasks such as identification, classification, and quantification across various medical imaging domains.

III. METHODOLOGY

Enhancing as well optimizing image processing system Using Deep Learning Multiple layers of interconnected neurons make up a Deep Neural Network (DNN) structure, a computational framework that is widely used for applications like speech recognition, picture recognition, and natural language processing [12]. Typically, one or more hidden layers, an input layer, and an output layer with neurons contribute to this architecture with neurons that process input data and produce values as an output. The initial input layer receives data, which could be images, audio signals, or text sequences, passing it to the subsequent hidden layer [13]. The hidden layer, in turn, processes this input data using learned parameters called weights and biases. Neurons within the hidden layer calculate their output by applying an activation function to the total weighted amount of their inputs, considering the interactions between neurons in the previous layer. The output layer is responsible for producing the model's final output, whether it's a classification label, regression value, or probability distribution [14]. It receives inputs from the last hidden layer and utilizes an appropriate activation function to yield the ultimate output. DNNs undergo training using a training dataset, learning to adapt their weights and biases to minimize a loss function. The variations in the results of output that the model predicted and the output that actually occurred is measured by this loss function [15].The optimization process leverages backpropagation to compute gradients of the loss function concerning model parameters, subsequently upgrading these parameters using an optimizer like stochastic gradient descent. DNN architectures are adaptable to fit particular use cases. Convolutional neural networks (CNNs), for example, are commonly used in image recognition tasks and have specialized layers for image processing, such as pooling and convolutional layers. Recurrent neural networks (RNNs), on the other hand, are frequently employed in natural language processing and have specialized layers like LSTM and GRU layers to handle sequential data [16]. Optimization Workflow for Deep Neural Networks in Image Quality Assessment is shown in Fig. 1.

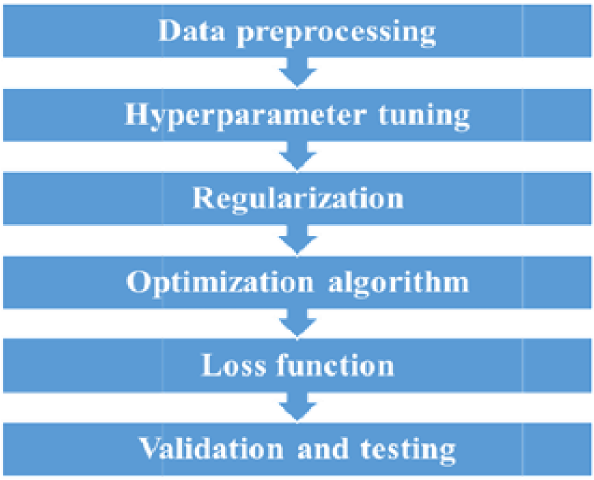

Fig. 1- Proposed Methodology

Data Pre-processing: This first action entails preparing the image data for training the DNN. To increase the training set's size and effectiveness, tasks such as image resizing, pixel value normalization, and data enhancement are performed [17]. Hyper parameter Tuning: The optimization of the DNN's performance necessitates adjustments to hyper parameters such as the amount of training rate of learning, epochs and amount of the batch. Techniques such as grid search, random searching, or Bayesian optimization can be applied to fine-tune these hyper parameters.

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Table 1 Comparing insights from review papers

Research Article	Principal Findings	Research Gaps
"Deeply-Recursive Convolutional Network for Image SuperResolution" J Kim et al (2017)	- Introduces a Comprehensively recursive network for ultra-high resolution. - Addresses training challenges.	- Further improvements in super-resolution quality.
"Accurate Image Super-Resolution Using Very Deep Convolutional Networks" By J Kim (2016)	- Utilizes super-resolution using deep convolutional networks. - Enhances accuracy and efficiency.	- Comparison with newer super-resolution techniques.
"Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network" By Christian Ledig (2017)	- Emphasizes perceptual quality in super-resolution. - Sets a new standard for realism.	- Evaluating computational efficiency.
"Diagnostic Image Quality Assessment and Classification in Medical Imaging: opportunities & challenges" By J J MA et al (2020)	-Draws attention to how crucial image quality is for imaging in medicine. - Calls for automated diagnostic image classification.	- Development of standardized image quality metrics.
"Learning Deep CNN Denoiser Prior for Image Restoration" By Kai Zhang et al (2017)	- Combines optimization and deep learning in order to restore images. - Uses CNN denoiser priors.	- Generalization to various image restoration tasks.
"Comparison of Full-Reference Image Quality Models for Optimization of Image Processing Systems "by Keyan Ding et al (2021)	- Enhances using objective image quality assessment. - Shows the applicability of IQA models in real-world scenarios.	- Exploration of novel IQA model properties.
"A Review of Deep Learning Approaches for Image Analysis" by Santhi N et al (2019)	Provides a comprehensive exploration of image analysis using deep learning techniques, focusing on image segmentation and computer-aided analysis	Could further investigate the specific deep learning models or algorithms that have shown the most promise in image segmentation and analysis.
"A review on deep learning in medical image analysis" by S. Suganyadevi et al (2022)	Discusses the significant impact of deep learning for images in medicine, enabling the identification, classification, and quantification of patterns in clinical images.	Could delve deeper into the specific challenges and limitations of medical image analysis employing deep learning.

Regularization Techniques: To prevent the DNN from over fitting to the training data, regularization methods like dropout and weight decay are employed. These techniques increase the DNN's generalization capabilities and its resilience to input data variations. Selection of Optimization Algorithm: The selection of the optimization method in a big way impacts the DNN's performance. Commonly used algorithms for DNN training consists of Stochastic Gradient Descent (SGD), Adam, and Adagrad. The choice is made in accordance with the particular specifications of the Image Quality Assessment (IQA) task. Loss Function Design: The loss function selected is critical in guiding the training process of the DNN for IQA. Frequently used loss functions in IQA include the structural similarity index (SSIM), mean squared error (MSE), and mean absolute error (MAE) [18]. The choice of the loss function should align with the desired qualities of the output quality score. Validation and Testing: Ensuring that the DNN generalizes well and doesn't over fit to the training data is crucial. Validation using a distinct validation dataset is carried out to confirm the model's performance. Subsequently, the optimized DNN is tested on a separate testing dataset to evaluate its effectiveness in handling new, unseen data [19].

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IV. RESULT & DISCUSSION

This review highlights the advancements in Image Quality Assessment (IQA) made possible by Convolutional Neural Architecture -based techniques. CNNs excel at handling complex image distortions like compression and noise, which are challenging for traditional IQA metrics such as MSE and PSNR. By automatically learning hierarchical representations of image data, CNNs can extract intricate features from large datasets, improving their accuracy in assessing image quality.

A key finding is the importance of using diverse metrics to evaluate CNN-based IQA models. Unlike traditional metrics, these models can be evaluated using metrics that align more closely with human perception, like Structural Similarity Index (SSI) and Mean Opinion Score (MOS), providing a more comprehensive assessment of image quality. The review emphasizes understanding the capabilities and limitations of CNN-based IQA models for effective integration into image processing systems, including image enhancement. While CNNs offer advantages, challenges like the requirement for large labeled datasets and transparency in decision-making need addressing for real-world deployment. Overall, this review underscores CNN-based IQA's potential to enhance image processing across industries. Future research can build on these findings to advance IQA and improve image processing systems.

V. CONCLUSION

The integration of image processing across industries underscores the critical role of accurate Image Quality Assessment (IQA) models, where traditional metrics like MSE and PSNR have limitations in human-perceived image quality assessment. This review has focused on the advancements and challenges of Convolutional Neural Network (CNN)-based IQA techniques, showcasing their potential to address complex distortions and improve overall assessment accuracy. Emphasizing the importance of diverse metrics for evaluating CNN-based models compared to traditional methods, this paper highlights the need to understand the capabilities and limitations of CNN-based IQA models for their effective integration into image processing systems across diverse domains, including image enhancement. By recognizing these aspects, future research can harness the full potential of CNN-based IQA techniques to enhance image processing systems and their applications in various industries.

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